Evaluating Manufacturing Success with Logistic Regression

September 28, 2019

1 Evaluating Semiconductor Manufacturing Success with Logistic Regression

In the following steps, a Logistic Regression model will be fit to predict failures in a semiconductor manufacturing facility. Because failures are typically not as frequent as many semiconductors are manufactured successfully, there will most likely be a class imbalance in the dataset that must be accounted for. To overcome this, SMOTE will be utilized to resample the training dataset and provide more failures to provide a more robust model to fit to the test dataset. Furthermore, because of the high volume of features used to describe the semiconductor manufacturing process, I also employed LASSO for feature selection to focus on only the features that provide the most impact to the manufacturing outcome. These selected features are also extremely useful information to understand which process levers are the most vital to the process. The company could then focus their efforts in improving these steps and subsequently will reduce failures.

2 Import data

The data must be imported along with the labels of each column. For now I've just named the features: feature1, feature2, and so on. These data were merged with the classification column (that holds the manufacturing outcome) and the date. All NA values were set to NaN for future imputation.

```
In [1]: # import semiconductor manufacturing features and label data
        import pandas as pd
        url_vars = "https://archive.ics.uci.edu/ml/machine-learning-databases/secom/secom.data"
        names = ["feature" + str(x) for x in range(1, 591)] # name each feature sequentially
        semi_vars = pd.read_csv(url_vars, sep=" ", names=names, na_values = "NaN")  # read in

        url_labs = "https://archive.ics.uci.edu/ml/machine-learning-databases/secom/secom_label
        semi_labs = pd.read_csv(url_labs,sep=" ",names = ["classification","date"],parse_dates
```

```
In [2]: # merge data and take a look at the first 5 rows
        semi = pd.merge(semi_vars, semi_labs,left_index=True,right_index=True)
        semi.head()
```

```
Out[2]:    feature1  feature2   feature3   feature4  feature5  feature6  feature7  \
        0   3030.93   2564.00  2187.7333  1411.1265    1.3602     100.0   97.6133
```

```
1   3095.78   2465.14  2230.4222  1463.6606    0.8294      100.0  102.3433
2   2932.61   2559.94  2186.4111  1698.0172    1.5102      100.0   95.4878
3   2988.72   2479.90  2199.0333   909.7926    1.3204      100.0  104.2367
4   3032.24   2502.87  2233.3667  1326.5200    1.5334      100.0  100.3967

   feature8  feature9  feature10  ...  feature583  feature584  feature585  \
0    0.1242    1.5005     0.0162  ...      0.5005      0.0118      0.0035
1    0.1247    1.4966    -0.0005  ...      0.5019      0.0223      0.0055
2    0.1241    1.4436     0.0041  ...      0.4958      0.0157      0.0039
3    0.1217    1.4882    -0.0124  ...      0.4990      0.0103      0.0025
4    0.1235    1.5031    -0.0031  ...      0.4800      0.4766      0.1045

   feature586  feature587  feature588  feature589  feature590  classification  \
0      2.3630         NaN         NaN         NaN         NaN              -1
1      4.4447      0.0096      0.0201      0.0060    208.2045              -1
2      3.1745      0.0584      0.0484      0.0148     82.8602               1
3      2.0544      0.0202      0.0149      0.0044     73.8432              -1
4     99.3032      0.0202      0.0149      0.0044     73.8432              -1

                 date
0 2008-07-19 11:55:00
1 2008-07-19 12:32:00
2 2008-07-19 13:17:00
3 2008-07-19 14:43:00
4 2008-07-19 15:22:00

[5 rows x 592 columns]
```

3 Clean the dataset

After taking a look at the first 5 rows, we can see that the data have been merged properly and get an idea of how the dataset is structured. There are a few steps we can take right away to clean up the dataset a bit. I started by imputing the NaNs within each feature with the median of the respective feature. Furthermore, I edited the classification column to be more straightforward by changing the name of the column to outcome and setting the successful manufacturing outcomes as 0 and the failures as a 1.

In [3]:
```
# replace missing values with the median of the column
semi.fillna(semi.median(), inplace=True)
# rename the classification column to outcome in order to be more representative of ma
semi.rename(columns={'classification': 'outcome'}, inplace = True)
# map the values of the outcome column to more interpretable 0 for success and 1 for f
semi['outcome'] = semi['outcome'].map({-1: 0, 1: 1})
```

4 Exploratory data analysis

Since the dataset describes the features that contribute to whether a semiconductor is successfully manufactured or not, I first wanted to see how the outcome was distributed. There is certainly a class imbalance within the manufacturing outcomes of this dataset with only about 100 failures out of over 1500 outcomes. This will be taken care of later on with SMOTE.

To get a general sense of the features in the dataset, I obtained the summary statistics and started to dig into a few features that seemed to have an interesting summary statistics. I plotted this histograms of a few features, feature 4 and 590 appear to be have a distribution that is skewed to the right and feature 6 appears to be made up of only one value for all runs. This is interesting to note because it will most likely be removed later since it is a constant that probably doesn't affect the manufacturing outcome.

I also plotted the manufacturing outcome as a time series to determine if there was a specific time where there was any clustering of the failures around specific time frames. There are so many rows of data it's a bit hard to parse through but there does seem to be quite a few failures in August and September of 2008.

```
In [4]: from matplotlib import pyplot as plt

        # plot a histogram of the manufacturing success
        plt.hist(semi['outcome'])
        plt.title('Distribution of Manufacturing Success and Failures')
        plt.ylabel('Count')
        plt.xlabel('Manufacturing Outcome')
        plt.show()
```

```
<Figure size 640x480 with 1 Axes>
```

```
In [5]: # get the exact number of manufacturing success and failures
        semi['outcome'].value_counts()
```

```
Out[5]: 0    1463
        1     104
        Name: outcome, dtype: int64
```

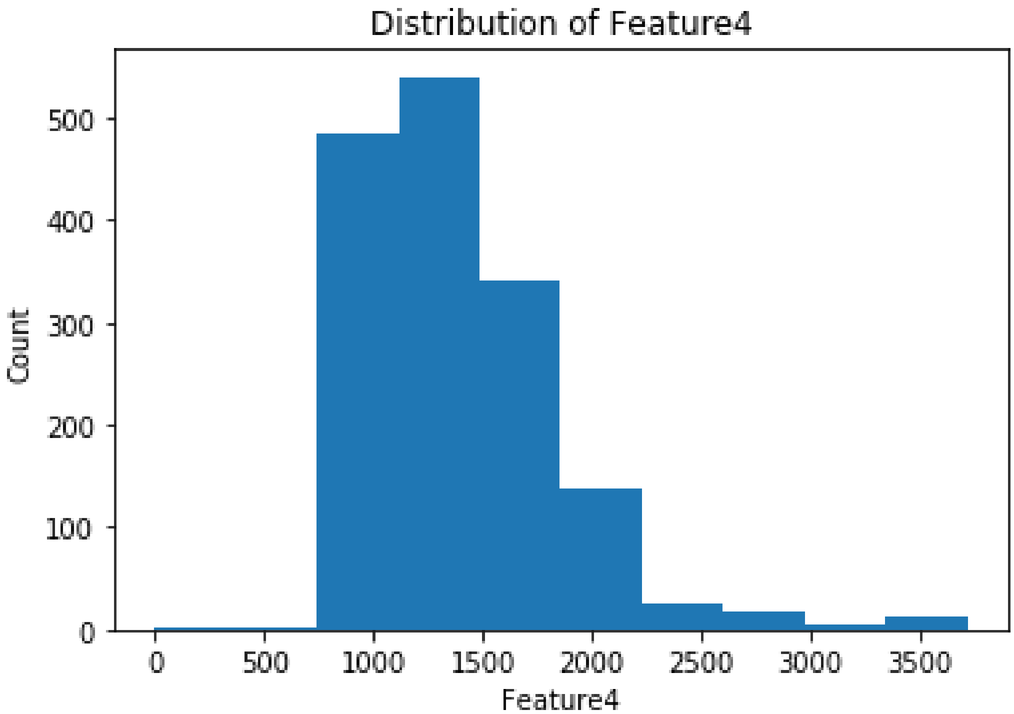
```
In [6]: # get the summary statistics for the entire dataset
        semi.describe()
```

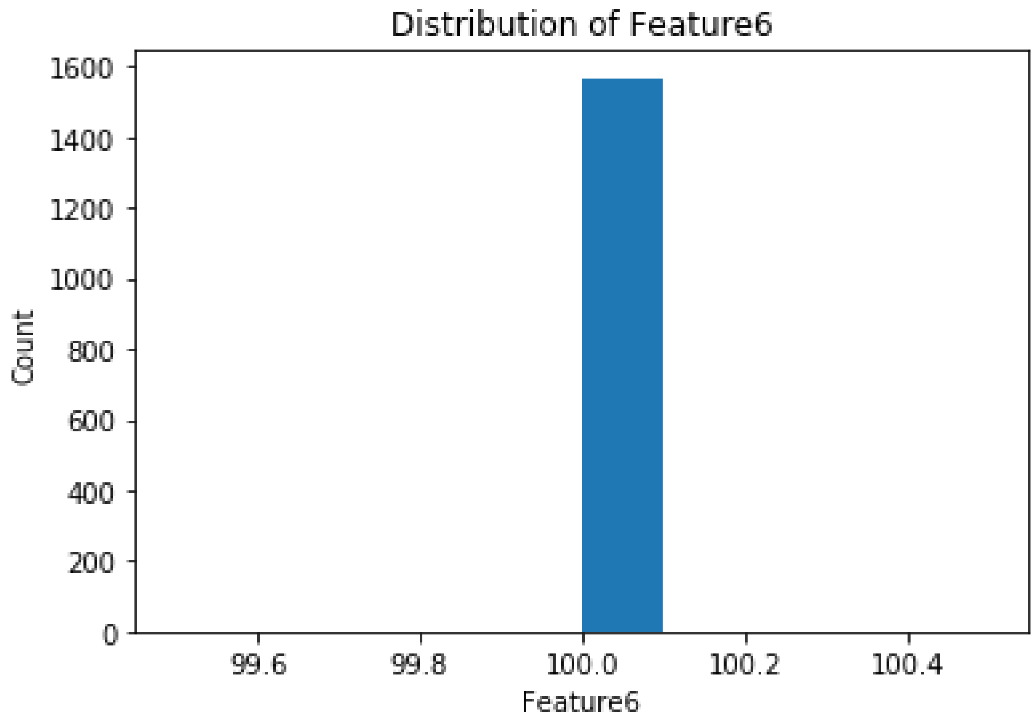
```
Out[6]:           feature1     feature2     feature3     feature4     feature5  \
        count  1567.000000  1567.000000  1567.000000  1567.000000  1567.000000
        mean   3014.441551  2495.866110  2200.551958  1395.383474     4.171281
        std      73.480841    80.228143    29.380973   439.837330    56.103721
        min    2743.240000  2158.750000  2060.660000     0.000000     0.681500
        25%    2966.665000  2452.885000  2181.099950  1083.885800     1.017700
        50%    3011.490000  2499.405000  2201.066700  1285.214400     1.316800
        75%    3056.540000  2538.745000  2218.055500  1590.169900     1.518800
        max    3356.350000  2846.440000  2315.266700  3715.041700  1114.536600
```

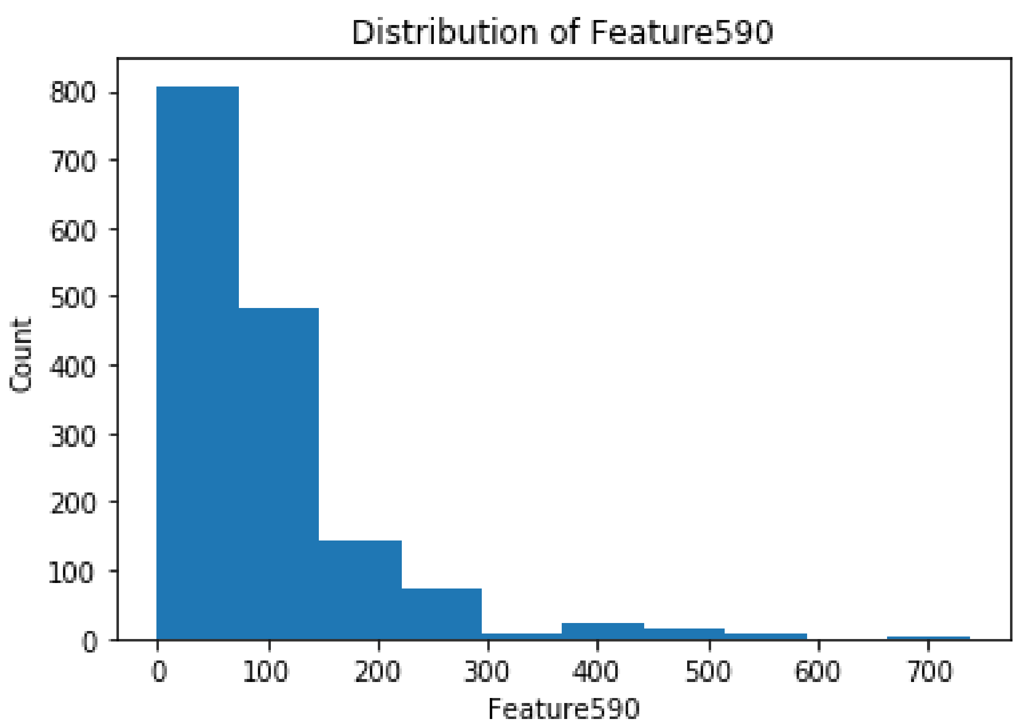
```
       feature6     feature7     feature8     feature9    feature10  ...  \
count    1567.0  1567.000000  1567.000000  1567.000000  1567.000000  ...
mean      100.0   101.116476     0.121825     1.462860    -0.000842  ...
std         0.0     6.209385     0.008936     0.073849     0.015107  ...
min       100.0    82.131100     0.000000     1.191000    -0.053400  ...
25%       100.0    97.937800     0.121100     1.411250    -0.010800  ...
50%       100.0   101.512200     0.122400     1.461600    -0.001300  ...
75%       100.0   104.530000     0.123800     1.516850     0.008400  ...
max       100.0   129.252200     0.128600     1.656400     0.074900  ...

        feature582   feature583   feature584   feature585   feature586  \
count  1567.000000  1567.000000  1567.000000  1567.000000  1567.000000
mean     82.403069     0.500096     0.015317     0.003846     3.067628
std      56.348694     0.003403     0.017174     0.003719     3.576899
min       0.000000     0.477800     0.006000     0.001700     1.197500
25%      72.288900     0.497900     0.011600     0.003100     2.306500
50%      72.288900     0.500200     0.013800     0.003600     2.757650
75%      72.288900     0.502350     0.016500     0.004100     3.294950
max     737.304800     0.509800     0.476600     0.104500    99.303200

        feature587   feature588   feature589   feature590      outcome
count  1567.000000  1567.000000  1567.000000  1567.000000  1567.000000
mean      0.021458     0.016474     0.005283    99.652345     0.066369
std       0.012354     0.008805     0.002866    93.864558     0.249005
min      -0.016900     0.003200     0.001000     0.000000     0.000000
25%       0.013450     0.010600     0.003300    44.368600     0.000000
50%       0.020500     0.014800     0.004600    71.900500     0.000000
75%       0.027600     0.020300     0.006400   114.749700     0.000000
max       0.102800     0.079900     0.028600   737.304800     1.000000

[8 rows x 591 columns]
```

In [7]:
```python
# plot a histogram of the distributions of a few features
# distribution of feature4
plt.hist(semi.feature4)
plt.title('Distribution of Feature4')
plt.ylabel('Count')
plt.xlabel('Feature4')
plt.show()

# distribution of feature6
plt.hist(semi.feature6)
plt.title('Distribution of Feature6')
plt.ylabel('Count')
plt.xlabel('Feature6')
plt.show()

# distribution of feature590
```

```
plt.hist(semi.feature590)
plt.title('Distribution of Feature590')
plt.ylabel('Count')
plt.xlabel('Feature590')
plt.show()
```




Distribution of Feature6
1600
1400
1200
1000
800
600
400
200
0
Count
99.6
99.8
100.0
100.2
100.4
Feature6


Distribution of Feature590
800
700
600
500
400
300
200
100
0
Count
0
100
200
300
400
500
600
700
Feature590

```
In [8]: # set the date column to be in the datetime format for time series analysis
        semi.loc[:, 'date'] = pd.to_datetime(semi.loc[:, 'date'])
        semi.set_index('date', inplace = True) # set index on dataset
        print(semi.head()) # print the beginning of the manufacturing dates
        print(semi.tail()) # print the end of the manufacturing dates
```

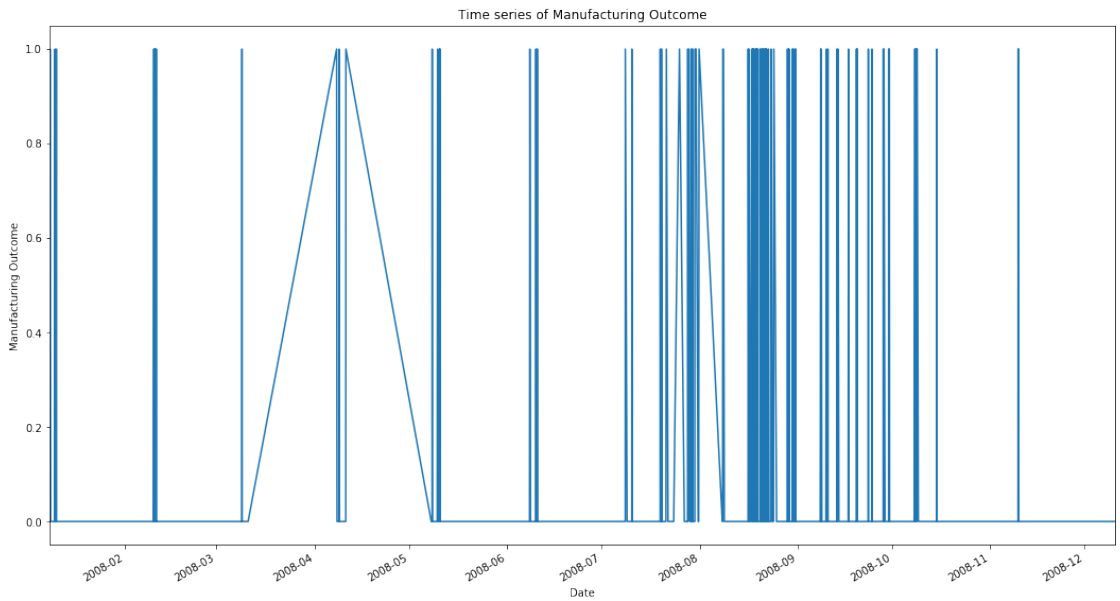
```
                     feature1  feature2   feature3   feature4  feature5  \
date
2008-07-19 11:55:00   3030.93   2564.00  2187.7333  1411.1265    1.3602
2008-07-19 12:32:00   3095.78   2465.14  2230.4222  1463.6606    0.8294
2008-07-19 13:17:00   2932.61   2559.94  2186.4111  1698.0172    1.5102
2008-07-19 14:43:00   2988.72   2479.90  2199.0333   909.7926    1.3204
2008-07-19 15:22:00   3032.24   2502.87  2233.3667  1326.5200    1.5334

                     feature6  feature7  feature8  feature9  feature10  ...   \
date                                                                    ...
2008-07-19 11:55:00     100.0   97.6133    0.1242    1.5005     0.0162  ...
2008-07-19 12:32:00     100.0  102.3433    0.1247    1.4966    -0.0005  ...
2008-07-19 13:17:00     100.0   95.4878    0.1241    1.4436     0.0041  ...
2008-07-19 14:43:00     100.0  104.2367    0.1217    1.4882    -0.0124  ...
2008-07-19 15:22:00     100.0  100.3967    0.1235    1.5031    -0.0031  ...

                     feature582  feature583  feature584  feature585  \
date
2008-07-19 11:55:00     72.2889      0.5005      0.0118      0.0035
2008-07-19 12:32:00    208.2045      0.5019      0.0223      0.0055
2008-07-19 13:17:00     82.8602      0.4958      0.0157      0.0039
2008-07-19 14:43:00     73.8432      0.4990      0.0103      0.0025
2008-07-19 15:22:00     72.2889      0.4800      0.4766      0.1045

                     feature586  feature587  feature588  feature589  \
date
2008-07-19 11:55:00      2.3630      0.0205      0.0148      0.0046
2008-07-19 12:32:00      4.4447      0.0096      0.0201      0.0060
2008-07-19 13:17:00      3.1745      0.0584      0.0484      0.0148
2008-07-19 14:43:00      2.0544      0.0202      0.0149      0.0044
2008-07-19 15:22:00     99.3032      0.0202      0.0149      0.0044

                     feature590  outcome
date
2008-07-19 11:55:00     71.9005        0
2008-07-19 12:32:00    208.2045        0
2008-07-19 13:17:00     82.8602        1
2008-07-19 14:43:00     73.8432        0
2008-07-19 15:22:00     73.8432        0

[5 rows x 591 columns]
                     feature1  feature2   feature3   feature4  feature5  \
```

```
date
2008-10-16 15:13:00   2899.41   2464.36  2179.7333  3085.3781    1.4843
2008-10-16 20:49:00   3052.31   2522.55  2198.5667  1124.6595    0.8763
2008-10-17 05:26:00   2978.81   2379.78  2206.3000  1110.4967    0.8236
2008-10-17 06:01:00   2894.92   2532.01  2177.0333  1183.7287    1.5726
2008-10-17 06:07:00   2944.92   2450.76  2195.4444  2914.1792    1.5978

                     feature6  feature7  feature8  feature9  feature10  ...  \
date                                                                    ...
2008-10-16 15:13:00     100.0   82.2467    0.1248    1.3424    -0.0045  ...
2008-10-16 20:49:00     100.0   98.4689    0.1205    1.4333    -0.0061  ...
2008-10-17 05:26:00     100.0   99.4122    0.1208    1.4616    -0.0013  ...
2008-10-17 06:01:00     100.0   98.7978    0.1213    1.4622    -0.0072  ...
2008-10-17 06:07:00     100.0   85.1011    0.1235    1.4616    -0.0013  ...

                     feature582  feature583  feature584  feature585  \
date
2008-10-16 15:13:00    203.1720      0.4988      0.0143      0.0039
2008-10-16 20:49:00     72.2889      0.4975      0.0131      0.0036
2008-10-17 05:26:00     43.5231      0.4987      0.0153      0.0041
2008-10-17 06:01:00     93.4941      0.5004      0.0178      0.0038
2008-10-17 06:07:00    137.7844      0.4987      0.0181      0.0040

                     feature586  feature587  feature588  feature589  \
date
2008-10-16 15:13:00      2.8669      0.0068      0.0138      0.0047
2008-10-16 20:49:00      2.6238      0.0068      0.0138      0.0047
2008-10-17 05:26:00      3.0590      0.0197      0.0086      0.0025
2008-10-17 06:01:00      3.5662      0.0262      0.0245      0.0075
2008-10-17 06:07:00      3.6275      0.0117      0.0162      0.0045

                     feature590  outcome
date
2008-10-16 15:13:00    203.1720        0
2008-10-16 20:49:00    203.1720        0
2008-10-17 05:26:00     43.5231        0
2008-10-17 06:01:00     93.4941        0
2008-10-17 06:07:00    137.7844        0

[5 rows x 591 columns]
```

In [9]:

```
# plot the manufacturing outcome as a time series
ax = plt.figure(figsize=(18, 10)).gca() # define plot
semi.outcome.plot(ax = ax) # plot manufacturing outcome
ax.set_xlabel('Date')
ax.set_ylabel('Manufacturing Outcome')
ax.set_title('Time series of Manufacturing Outcome')
```

Out[9]: Text(0.5, 1.0, 'Time series of Manufacturing Outcome')



5 Prepare the data for modeling

After cleaning and getting to know the dataset a bit more, I now need to start preparing the dataset for modeling. First, I identify the outcome column as the target we are trying to predict and determine that the features will be made up of the rest of the columns in the dataset.

Next, the dataset is split up into training and test datasets further subsetted by their features and targets. The test dataset is made up of 20% of the original dataset.

```
In [10]: # establish target and features of the manufacturing data
         # set the target to the encoded manufacturing outcome column
         target = semi[['outcome']]
         # set the features as the rest of the dataset after dropping the features that are no
         feats = semi.drop(['outcome'], axis=1)
```

```
In [11]: from sklearn import model_selection

         # split original data into training and test sets
         feat_train, feat_test , target_train, target_test = model_selection.train_test_split(
                                                              test_size=0.2, random_state=6)
```

6 Perform initial Logistic Regression model

I wanted to see how the model performed without handling the class imbalance or selecting specific features. I employed a Logistic Regression model on the training data and was about 95%

accurate. This is a really good score but is most likely not very representative of the actual ability to detect failures due to the class imbalance. I will use the SMOTE method to resample the dataset and test the model performance again.

```
In [12]: from sklearn.linear_model import LogisticRegression

         # instantiate logistic regression model and fit to train dataset
         clf = LogisticRegression()
         logR = clf.fit(feat_train, target_train)
         # get the accuracy of the dataset
         logR.score(feat_train, target_train)
```

```
/Users/caseythayer/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433:
  FutureWarning)
/Users/caseythayer/anaconda3/lib/python3.6/site-packages/sklearn/utils/validation.py:761: Data
  y = column_or_1d(y, warn=True)
/Users/caseythayer/anaconda3/lib/python3.6/site-packages/sklearn/svm/base.py:931: ConvergenceWa
  "the number of iterations.", ConvergenceWarning)
```

```
Out[12]: 0.9497206703910615
```

7 Handling class imbalance with SMOTE

I use the SMOTE method to resample the training dataset and increase the number of failures within the dataset. This allows the model to train on more data that can help predict failures better. The resampled training data are then fed through the a Logistic Regression model again. This time the accuracy is a bit higher than before at about 96%. Because we used SMOTE, this model is a bit more representative of predicting manufacturing failures. The next step will be fine tuning the model with feature selection to see if we an improve the model further and provide the company with the features that are most vital to manufacturing failures.

```
In [13]: import imblearn
         from imblearn.over_sampling import SMOTE
         # handle class imbalance using SMOTE
         sm = SMOTE(random_state=42)
         X_res, y_res = sm.fit_sample(feat_train, target_train)
```

```
/Users/caseythayer/anaconda3/lib/python3.6/site-packages/sklearn/utils/validation.py:761: Data
  y = column_or_1d(y, warn=True)
```

```
In [14]: # instantiate logistic regression model and fit to resampled training dataset
         clf = LogisticRegression()
         logR = clf.fit(X_res, y_res)
         # get accuracy of the model
         logR.score(X_res, y_res)
```

```
/Users/caseythayer/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433:
  FutureWarning)
/Users/caseythayer/anaconda3/lib/python3.6/site-packages/sklearn/svm/base.py:931: ConvergenceWa
  "the number of iterations.", ConvergenceWarning)
```

```
Out[14]: 0.9597946963216424
```

8 Feature selection with LASSO

I used LASSO to select the most important features of the manufacturing dataset and used them to run another Logistic Regression model. LASSO selects the most important features by shrinking the coefficients of irrelevant features to 0 so they have little impact on the model. I still used the resampled training data obtained using SMOTE because it is more representative of data containing more failures. The model improved when using the selected features, as expected, to provide an accuracy of about 99%.

```
In [15]: # instantiate Logistic Regression model employing LASSO for feature selection
         clf = LogisticRegression(penalty = 'l1')
         # fit model to resampled training dataset
         logR = clf.fit(X_res, y_res)
         # get the accuracy of the model
         logR.score(X_res, y_res)
```

```
/Users/caseythayer/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433:
  FutureWarning)
/Users/caseythayer/anaconda3/lib/python3.6/site-packages/sklearn/svm/base.py:931: ConvergenceWa
  "the number of iterations.", ConvergenceWarning)
```

```
Out[15]: 0.9850299401197605
```

9 Conclusion

Predicting semiconductor manufacturing failure rates requires quite a few steps to get to a representative and robust model. In this case study, I cleaned the dataset, performed some EDA and prepared the data for modeling. Next, I evaluated a Logistic Regression model with a number of steps to improve it's ability to predict manufacturing failures. First, I tested the model without changing anything to figure out what the starting point was and how the model was performing straight up (accuracy around 96%).

Through EDA, I observed a class imbalance in the manufacturing outcome. I handled the class imbalance by employing SMOTE to resample the test dataset and provide more data to train on. I tested the model again with the resampled data and found the model accuracy decreased a bit, which was expected (94%). The resampled data provides a more representative number of failures to train on so it helps train the model in a more realistic sense.

Finally, I used LASSO to select the most important features. LASSO selects the most vital features by setting the coefficients of the irrelevant features to 0 and therefore, removing their impact on the model. After performing LASSO, I fit the model to the resampled data again and found that it improved the accuracy even more (99%). In addition, the list of most important features can be provided to the company to guide future improvements in the process and prevent failures.